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A new parallel decision support system (P-CoMG) to assist decisions in power networks

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Abstract

Power system expansion specifically for distribution networks is gaining more importance due to the integration of distributed energy systems. Optimisation models are more used to tackle generation and transmission expansion problems (GTEP). This way, cloud computing, machine learning, big data, internet of things, simulation and optimisation are critical factors in the innovation of the power sector. In the recent past, a new inter-disciplinary subject focusing on energy and information system called energy informatics has emerged. This paper proposes a novel mathematical model to deal with GTEP regarding the collaboration and competition between all the nodes and actors in the power network. Additionally, this work proposes the usage of a parallel algorithm to solve the GTEP problem using the model efficiently. This way, to assist power network companies to make better strategic, tactical and operational decisions related to the investments, maintenance or evaluation of the power network a cloud-based Decision Support System (DSS) is proposed. Mainly, focused at: (i) integrate the data in the system, (ii) integrate the model, (iii) automate the resolution process, and finally present the results in an interactive way to the end-users. This work extends the advantages of optimisation and simulation models with the potential of parallel and cloud computing to automate and offer the knowledge and the analytics. The results show that the decision support system proposed helps decisions makers in real situations to do better planning by obtaining the competitive advantages of using the proposed model in a usable, flexible and straightforward way.

Keywords: Energy informatics, Generation transmission expansion problem, Decision Support System, Transactive energy

1. Introduction

The GTEP (Generation and Transmission Expansion Problem) is a classic problem in the field of power system [1]. This problem deals with optimal investment for expansion of the existing power network through transmission lines and installation of new generation units to meet the demand. Typically it is a node-arc formulation with a mass balance constraint confirming the total power generated is equals to the energy consumed. There are multiple versions of the problem namely: considering the circuit theory (Alternating current (AC), Direct current (DC)) version, higher granularity version considering the hourly resolution and details of the network topology, low granularity based considering a larger network [2, 3, 4, 5, 6, 7]. The transition from traditional conventional resources based centralized power network to the carbon neutral decentralized and distributed renewable form of power generation [8] requires an alternative approach to the classical method for solving a GTEP.

In addition to that the rising number and types, the nature of resources, consumer participation and the growing electricity demand apart from the purely economic boost and growth in information and communication technologies (peer-peer interactive) to alternative resources are the reasons to reiterate the approach to solving the problem [9, 10].

Hence, GTEP is one of the central problems in the domain of Energy informatics (Ei) [11, 12, 13]. Energy informatics deals with the ICT (information and communication technologies) and intelligent embedded electronic devices applications to improve the energy generation, transmission, distribution and consumption in one platform. The energy transition has brought the distribution system at the forefront. Primarily due to renewable injection and interactive consumer participation. The function of a distribution system expansion problem is the same as that of the GTEP. However, the number of system operators is high in comparison to transmission in a given country. With more operators comes to the challenge of coordination in investment decisions considering the decision of one affects the others. Secondly, it brings about a local electricity market.

Multi-period distribution system expansion planning models are presented in [14, 15, 16, 17, 17, 18, 19]. A review of different expansion planning models are presented in [20, 21, 22]. An co-optimisation model for microgrid GTEP is presented in [23].

The main contribution of this work is developing a mathematical model aimed at solving the problem and also putting complex methods and algorithms as a service of the society naturally and automatically to support the decisions related to power industry and smart cities.

Practical and industrial applications of GTEP model relies on a balance between complexity and execution time. The complexity refers to the granularity of the model. The granularity of the system is very important to take an optimal decision in a power distribution network. Moreover, with the increase in the number of sub-networks, the system becomes intractable due to combinatorial explosion. Nevertheless, application of a model in industry meaning data input from various departments and results in an easily comprehensible format. The complexity and size of the problem become intractable with sufficient details. A renewable energy allocation planning considering dynamic grid topology is presented here [24]. Therefore, to deal with the real issues this paper proposes the use of a smart parallel algorithm to overcome the combinatorial explosion and reduce the complexity.

A big data approach for decision support system in Stockholm is presented here [25]. Planning support system for smart cities is described here [26]. Moreover, a DSS for GTEP is presented here [27] and [28]. Inspired by these works, in this paper, we present a decision support system (DSS) oriented to help smart cities and electrical companies in the design, expand and maintenance of the power network. One of the main contributions is grant access to a DSS capable of recommending prescriptions regarding optimal solutions and evaluate predictions concerning what if and scenarios analysis. For example, if the company want to make a new investment in generation capacity then the company explores multiple possibilities to choose from with investment repercussions. The company can study the comparative solutions of different investments.

The novelty of this work is developing a Software-as-a-service (SAAS) capable of integrating the data, the mathematical model, the parallel tools in such a way that the society can interact with. The main advantage of cloud computing is to spot the barrier to scale the computing power needs.

In this work, a coordinated multi-period GTEP formulation namely coordinated microgrid expansion planning is presented. The CoMG coordinated operational information such as energy requirements or affability to perform transactions. A parallelization framework is developed (R-CoMG) and applied through high-performance computers. Finally, a novel DSS for power network investment decision making is implemented (P-CoMG).

The remainder of the paper is organized as follows: Section 2 presents an overall vision of related work in power energy field and decision support system. Section 3 presents a coordinated multi-period GTEP deterministic model. Section 4 presents a method to solve the model to optimality and the parallel approach to boost the resolution. Then, in Section 5 is described the Decision Support System that orchestrates the integration, the resolution and the visualisation of the GTEP problem. In Section 6 the results from a real case study are evaluated and discussed. Finally, Section 7 outlines the main conclusions and future work.

2. Related Work

This section presents a literature review and other related papers concerning the application used in this work and the development of decision support systems in the power and energy field.

In this field, is very important to understand the impact and the influence of decisions on buyers and energy sellers [29], energy scheduling [30], or exploring new alternative market models [31]. This way research on optimisation and simulation models is crucial in the current days.

Simulation and predictive analytics are more and more studied due to the high uncertainty surrounding these fields, see [32] and [33]. Moreover, predictive models allow the study of future changes to the real systems and their behaviour, reducing the costs and time needed to perform upgrades This way, decision-makers can assist and mitigate the unexpected effects and risks of decision making. Furthermore, authors in [34] propose a predictive software for modelling microgrids with or without grid connection.

Many prescriptive models have been proposed to deal with the complexity of power and energy systems. Nowadays, the more common ones are based on a multi-agent architecture, see [35]. This way, several authors research aimed at minimising the consumption, minimising the impact on the environment, minimising the energy sharing, the transportation or the costs, see [36], [37] and [38]. In all the models, the decision is left for the system operator. Therefore, it is essential to transfer this technical knowledge to system operators and power supply companies.

Although there are a lot of prescriptive and predictive models in academic research, real companies only have access to a minimal range of them. The main problem is the lack of automation and integration of these models in useful tools or decision support system that leads the assistance and the knowledge to the companies. In power and energy systems, DSSs are gaining popularity in the last years. A decision support system (DSS) is a set of smart tools designed to assist with knowledge, information and analytics in any decision-making process, see [39]. Therefore, they are information systems that integrate dedicated informatics objects for decision assistance and general instruments as a fundamental part of the global system, see [40].

The majority of the works found in the current literature are aimed to assure the adequacy and the production of the power system. Authors in [41] propose a DSS to evaluate biomass production in the power system. Recently, in [42] authors propose a DSS to assist in the green production of wind generators. Other works are focused on solving issues related to the reconfiguration of the power distribution [43], power grid faults [44] or to control the voltage of a renewable energy system. Nevertheless, for the GTEP we did not found any suitable proposal.

Finally, in order to identify the current state-of-the-art on DSS, we have surveyed what commercial applications are offering at the moment. One of the most successful applications used in Norway is SafeMon [45] that provides power supply companies with simulations, predictions and real-time information to control the flow and the relations between elements. Moreover, many companies are using many tools with consumption statistics, real-time demand, predictions models, customer trends and behaviour, blockchain with information about the current network and more. One of the main challenges in this field is to extend this information with prescriptive models to automate the decision-making process. Another important challenge is integrated all these tools in a decision support system to assist the decision using smart data automatically.

3. Coordinated microgrid expansion planning (CoMG)

The coordinated microgrid expansion planning (CoMG) is an expansion planning model. In literature it is referred as a GTEP. It is a node-arc based model. Each node consists of load demand, generation units and energy storage units. Two types of generation units are considered: dispatchable and non-dispatchable. The dispatchable generation has a unit commitment process that includes the minimum on and off time, the cost involved in switching on and keep an unit in on state. The non-dispatchable generation is uncontrollable as it is nature dependent. Wind energy is considered for this purpose. For energy storage units battery banks are considered. The operation of the battery banks are evaluated though state of the charge (SOC), extraction and injection of energy to a node.

3.1. Mathematical Model

In this section, we present a novel deterministic formulation for solving the generation and transmission expansion planning problem (GTEP). The objective function in Equation (1a) states to minimize the overall cost function. This function represents the difference between investment cost C^{inv} and operational cost C^{opr}.

$$(GTEP) \quad min \quad C^{inv} - C^{opr} \tag{1a}$$
$$s.t$$

$$\sum_{g} PG_{g,i}^{t} * ExistingConvGen_{g,i} + \sum_{w} PW_{w,i}^{t} + PNW_{i}^{t}$$
$$- \sum_{j} F_{i,j}^{t} * ExistingArcs_{i,j} + \sum_{j} F_{j,i}^{t} * ExistingArcs_{i,j}$$
$$- \sum_{j} F_{i,j}^{t} * PotentialArcs_{i,j} + \sum_{j} F_{j,i}^{t} * PotentialArcs_{i,j}$$
$$+ \sum_{s} XBatOUT_{s,i}^{t} - XBatIN_{s,i}^{t} - EnSold_{i}^{t} + FlowA_{i}^{t} + FlowB_{i}^{t} = Dem_{i}^{t}$$
$$\forall i, j \in N, t \in T \mid PotNode_{i} = 0 \tag{1b}$$

$$Fmin_{i,j} \geq F_{i,j}^{t} \leq Fmax_{i,j} \quad \forall i, j \in N, t \in T \mid Ae_{i,j} = 1 \ \vee \ Ap_{i,j} = 1 \tag{1c}$$

$$F_{i,j}^{t} \leq M * dir_{i,j}^{t} \quad \forall i, j \in N, t \in T \tag{1d}$$

$$F_{j,i}^{t} \leq M * \left(1 - dir_{i,j}^{t}\right) \quad \forall i, j \in N, t \in T \tag{1e}$$

$$F_{i,j}^{t} * PotentialArcs_{i,j} \leq Y_{i,j} * PotentialArcs_{i,j} * Fmax_{i,j} \quad \forall i, j \in N, t \in T \tag{1f}$$

$$FlowA_{i}^{t} \leq ExcCapA_{i}^{t} \quad \forall i \in N, t \in T \tag{1g}$$

$$FlowB_{i}^{t} \leq ExcCapB_{i}^{t} \quad \forall i \in N, t \in T \tag{1h}$$

$$Yon_{g,i}^{t} \leq ExistingConvGen_{g,i} \geq Ygen_{g,i}^{t} \quad \forall \, g \in G, i \in N, t \in T \tag{1i}$$

$$\begin{aligned} & Pmin_{g} * Ygen_{g,i}^{t} * ExistingConvGen_{g,i} \leq PG_{g,i}^{t} \\ & \leq Pmax_{g}^{t} * Ygen_{g,i}^{t} * ExistingConvGen_{g,i} \quad \forall \, g \in G, i \in N, t \in T \end{aligned} \tag{1j}$$

$$Ygen_{g,i}^{t} - Ygen_{g,i}^{t-1} = Yon_{g,i}^{t} - Yoff_{g,i}^{t} \quad \forall \, g \in G, i \in N, t \in T \tag{1k}$$

$$Yon_{g,i}^{t} \leq (1 - Yoff_{g,i}^{t}) * M \quad \forall g \in G, i \in N, t \in T \tag{1l}$$

$$\sum_{t+1}^{min\,(u^{on})} Ygen_{g,i}^{t} \geq min\,(l^{on}) * Yon_{g,i}^{t} \quad \forall \, g \in G, \ i \in N, \ t \in T \tag{1m}$$

$$\sum_{t+1}^{min\,(u^{off})} Ygen_{g,i}^{t} \leq min\,(l^{off}) * \left(1 - Yoff_{g,i}^{t}\right) \quad \forall \, g \in G, \ i \in N, \ t \in T \tag{1n}$$

$$K_{i} \leq maxWcap_{i} \quad \forall \, i \in N \tag{1o}$$

$$PNW_{i}^{t} \leq K_{i} * PercW_{i}^{t} \quad \forall \, i \in N, t \in T \tag{1p}$$

$$PW^t_{w,i} \leq Wmax^t_{w,i} * PercW^t_i \quad \forall\, w \in W, i \in N, t \in T \tag{1q}$$

$$PotBat_{s,i} * M \geq QtyBat_{s,i} \quad \forall s \in S, i \in N \tag{1r}$$

$$CharBat^t_{s,i} \leq QtyBat_{s,i} * MaxBat_s + MaxBat_s * QtyExistBat_{s,i} \quad \forall s \in S, i \in N, t \in T \tag{1s}$$

$$QtyBat_{s,i} \geq PotBats, i \quad \forall s \in S, i \in N \tag{1t}$$

$$1 - ExistBat_{s,i} \geq Potbat_{s1,i} \quad \forall s, s1 \in S | s \neq s_1 \tag{1u}$$

$$CharBat^t_{s,i} = CharBat^{t-1}_{s,i} - XBatOUT^t_{s,i} * (1/Ebat_s) + XBatIN^t_{s,i} \quad \forall s \in S, i \in N, t \in T | t > t_1 \tag{1v}$$

$$CharBat^t_{s,i} = MaxBat_s * QtyBat_{s,i} + MaxBat_s * QtyExistBat_{s,i} - XBatOUT^t_{s,i} * (1/Ebat_s) + XBatIN^t_{s,i} \quad \forall s \in S, i \in N, t \in T | t = 11 \tag{1w}$$

$$CharBat^t_{s,i} \geq MinBat_s * \Bigg(QtyBat_{s,i} * MaxBat_s + MaxBat_s * QtyExistBat_{s,i} \Bigg) \quad \forall s \in S, i \in N, t \in T \tag{1x}$$

$$XBatOUT^t_{s,i} * (1/Ebat_s) \leq RateBat_s * \Bigg(QtyBat_{s,i} * MaxBat_s + MaxBat_s * QtyExistBat_{s,i} \Bigg) \quad \forall s \in S, i \in N, t \in T \tag{1y}$$

$$XBatOUT^t_{s,i} \leq RateBat_s * \Bigg(QtyBat_{s,i} * MaxBat_s + MaxBat_s * QtyExistBat_{s,i} \Bigg) \quad \forall s \in S, i \in N, t \in T \tag{1z}$$

$$XBatIN^t_{s,i} \leq RateBat_s * \Bigg(QtyBat_{s,i} * MaxBat_s + MaxBat_s * QtyExistBat_{s,i} \Bigg) \quad \forall s \in S, i \in N, t \in T \tag{1aa}$$

Equation (2) presents the formulation to evaluate the total investment (C^{inv}). This equation can be broken down into three parts: new investment in wind, battery units and new transmission links. First of all, the cost to install a new wind turbine K_i is the multiplication of cumulative unitary investment factor $CRFwind$ with the individual cost of a particular wind turbine $InvW_i$. The second term depicts the investment in some battery units $QtyBat_{s,i}$. Therefore, the single cost of a battery unit $QtyBat_{s,i}$ is multiplied by a unitary battery cost $CRFBat_S$. Similarly, the final term represents the investment in transmission. $CRFcables$ models the unitary cost of transmission while $Y_{i,j}$ is a new transmission line between the node i and the node j. Moreover, $ArcCost_{i,j}$ represents the cost of connecting these nodes.

$$
\begin{aligned}
C^{inv} = \Bigg(\sum_{i} CRFwind * InvW_i * K_i + \sum_{s,i} CRFBat_s * QtyBat_{s,i} * Cbat_s \\
+ \sum_{i,j|i \neq j} CRFcables * Y_{i,j} * ArcCost_{i,j} \Bigg)
\end{aligned}
\tag{2}
$$

Equation (3) revokes the operational cost of the microgrid C^{opr}. The operational cost is only applicable to the dispatchable generator g and battery units s. The maintenance cost for wind is inclusive of the investment cost for each turbine.

$$
\begin{aligned}
C^{opr} = \Bigg(\sum_{i} CRFwind * InvW_i * K_i + \sum_{s,i} CRFBat_s * QtyBat_{s,i} * Cbat_s \\
\sum_{i,j|i \neq j} CRFcables * Y_{i,j} * ArcCost_{i,j} \Bigg)
\end{aligned}
\tag{3}
$$

Let us start to consider the constraints. First of all, the formulation of mass balance for the node and edge-based power network is presented; see Equation (1b). Specifically, the quantum of production and consumption must be equal for each node i and period t. In the model, there are three mass balance formulations as in Equation (4). The first one applies when an optimal decision is made for self-contained GTEP i.e., without considering the potential connection with other MG in the environment. Nevertheless, in the coordination mode (where $PotNode_i = 1$) there are an upper and a lower bound for the mass balance formulations. One states the total production must be greater than or equals to the total demand Dem_i^t multiplied by the percentage of demand $PercDem_i^t$. The other confirms that the total production doesn't exceed the maximum demand at each time t for each node i.

$$
\begin{cases}
0, & \text{self contained mode } L.H.S = Dem_i^t \\
1, & \text{coordination mode } L.H.S \geq Dem_i^t \times PercDem_i^t \ \& \ L.H.S < Dem_i^t
\end{cases}
\tag{4}
$$

In Equation (1c) the flow $F^t_{i,j}$ is restricted within the maximum $Fmax_{i,j}$ and minimum $Fmin_{i,j}$ for each existing $Ae_{i,j}$ and potential transmission lines $Ap_{i,j}$. That is to bind the flow within the maximum flow capacity of the transmission lines of the power network for each node i, j at period t. Next, Equations (1d and 1e) invoke the mutually exclusive flow principle through a disjunctive formulation. Furthermore, it is important to ensure that the flow in potential arcs $PotentialArcs_{i,j}$ is less than or equals to the maximum capacity of the new transmission line $Y_{i,j} \times Fmax_{i,j}$, see Equation (1f). The maximum flow from dispatchable and renewable resources $FlowA^t_i$, $FlowB^t_i$ are restricted with the upper bound of the maximum capacity of the resource capacities $ExcCapA^t_i$, $ExcCapB^t_i$ respectively.

Quite apart from this, Equations (1i -1n) outlines the restrictions for the operation of disputable generators. First of all, Equation (1i) restricts that the existing dispatchable generator is active and producing for each generator g. Furthermore, the production $PG^t_{g,i}$ is constrained within the upper limit of maximum capacity $Pmax^t_g$ and lower limit $Pmin_g$ while the generator is working $Ygen^t_{g,i}$, see Equation (1j). The generator status is mutually exclusive, or in other words, it can't be in both on and off states at the same time; Equations (1k , 1l). Finally, a unit commitment formulation for the generator is presented in Equations (1m and 1n).

The terms $u^{on}, u^{off}, u^{off}, l^{off}$ outline the upper and lower bounds for the status length of the generator, see Equation (5)

$$
\begin{aligned}
u^{on} &= \left[Th \ \vee \ (t + \ MinOn_g - 1)\right] \\
l^{on} &= \left[\Big(MinOn_g - 1\Big) \vee \ \Big(Th - t\Big)\right] \\
u^{off} &= \left[Th \ \vee \ (t + \ MinOff_g - 1)\right] \\
l^{off} &= \left[\Big(MinOff_g - 1\Big) \vee \ \Big(Th - t\Big)\right]
\end{aligned}
\tag{5}
$$

The new installation of the wind turbine units K_i are restricted within the available turbine capacities $maxWcap_i$; Equation (1o). Next, Equation (1p) production from new wind turbine $PNW^t_{w,i}$ is restricted within production curve of the turbine type $PercW^t_i$. Similarly, the production $PW^t_{w,i}$ from the existing renewable resource is restricted within the maximum capacity $Wmax^t_{w,i}$, see Equation (1q).

Another important block of constraints, Equations (1r to 1aa), are related to the battery banks. First, Equation (1r) applies the restriction to install a minimum quantity of battery units $QtyBat_{s,i}$. Next, in Equation (1s the battery discharge $CharBat^t_{s,i}$ is restricted within the maximum capacity of battery bank

$MaxBat_s \times QtyExistBat_{s,i}$. Moreover, the quantity of battery installed $QtyBat_{s,i}$ is restricted within the upper bound $PotBats, i$; Equation(1t). In Equation (1u) the mutual exclusive property of potential battery unit installation $PotBats, i$ is formulated. This way, the state of charge of battery $CharBat^t_{s,i}$ refers to the available capacity of battery that can be discharged, and is the difference between the discharge $XBatOUT^t_{s,i}$ and charge $XBatIN^t_{s,i}$ of battery bank as in Equation (1v). Equation (1w) states the initial state of charge of battery unit. Hence, the minimum capacity of battery $MinBat_s$ is formulated in Equation (1x). The last but not the least, Equations (1y and 1aa) models the rate of discharge and charge of battery respectively.

The unitary cost of investment is calculated through the capital recovery factor as authors in [46] proposed. The mathematical models for battery, renewable and transmission lines are presented in Equations (6a , 6b and 6c) respectively.

$$CRFbat = \left[\frac{Interest * (1 + Interest)^{LifeBat_s}}{(1 + Interest)^{LifeBat_s - 1}} \right] \qquad \forall s \in S \tag{6a}$$

$$CRFwind = \left[\frac{Interest * (1 + Interest)^{LifeWind}}{(1 + Interest)^{LifeWind-1}} \right] \tag{6b}$$

$$CRFcables = \left[\frac{Interest * (1 + Interest)^{LifeCables}}{(1 + Interest)^{LifeCables-1}} \right] \tag{6c}$$

The energy not utilized from dispatchable is formulated through $ExEnRen^t_i$, see Equation (7).

$$ExEnRen^t_i = \sum_{w \in W} \left(Wmax^t_{w,i} - PW^t_{w,i} \right) + \left(K_i * PercW^t_i - PNW^t_i \right) \quad \forall i \in N, t \in T \tag{7}$$

Similarly, the energy not used from renewable is modelled by $ExEnCon^t_i$, see Equation (8).

$$ExEnCon^t_i = \sum_{g \in G} \left(Pmax^t_g * ExistingConvGen_{g,i} * Ygen^t_{g,i} \right) - PG^t_{g,i} \quad \forall i \in N, t \in T \tag{8}$$

For instance, if the capacity of the dispatchable generator is 100 MW and the production is 50MW, then there is a potential 50% energy utilisation.

4. Collaborative Microgrid Resolution Method (R-CoMG)

Consider the following power network depicted in Figure 4 formed by different nodes and grouped in different microgrids; where each colour represents a microgrid. Furthermore, the arrows represent the energy demand of the node, the battery icon represents the capacity of the node to store energy, and the other symbols represent the capacity of the node to generate energy; from wind generators or conventional generators.This way, each microgrid can be modelled using the mathematical model described in Section 3.

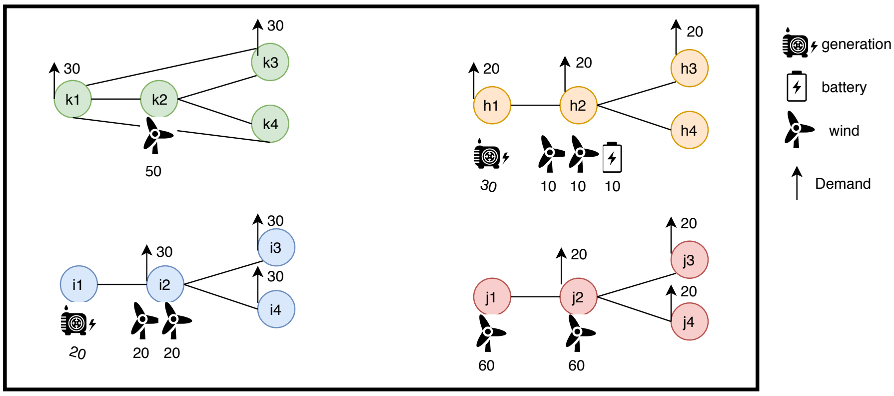
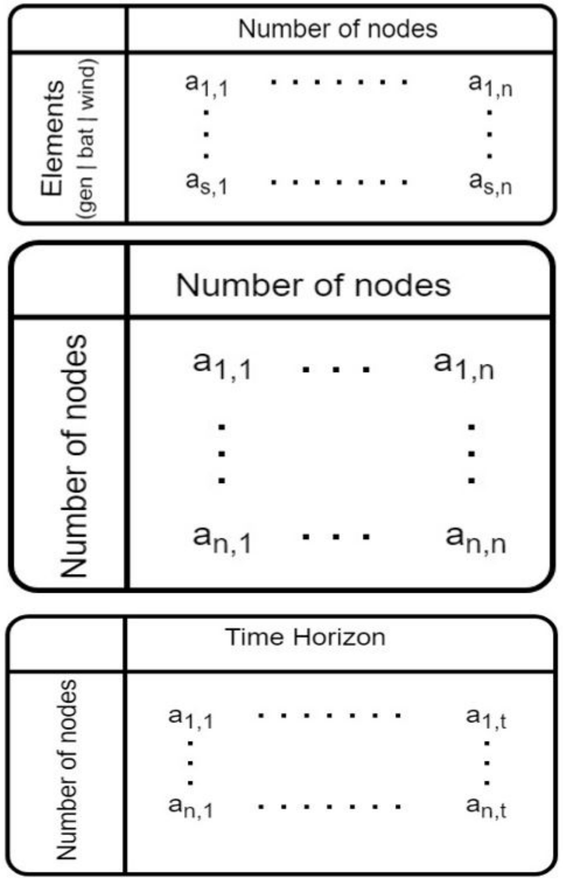


Figure 1: Example of a small general power network highlighting all the elements and the different microgrids.

To solve this GTEP problem each microgrid needs to consider not only its solution but also the solution of the other microgrids.

This way, the resolution procedure is based on an iterative solving of instances, sharing solutions, and updating instances until all the permutations are evaluated. The most important part of this procedure is the update step. In this step, a solved instance shares its solution to a goal instance to update its values. The main theoretical premise behind this update is that a solved instance has very important information in the variables ExEnRen, ExEnCon and EnSold representing the excess of renewable energy, the excess of conventional energy and the amount of energy sold. Based on this information the number of nodes in the goal instance could increase to share this energy. There is overwhelming evidence for the notion that if we introduce new nodes to share energy, the information related to these nodes has to be copied from the solved instance to the goal instance increasing the number of wind generators, batteries or conventional generators and all the parameters related to them. Furthermore, the network parameters are updated to consider new



Parameter	Row value (Element e, nodes [1,n])
ExistingConvGen	solved.ExistingConvGen[n1] else: 0
ExistBat	solved.ExistBat[n1] else: 0
QtyExistBat	solved.QtyExistBat[n1] else: 0
ExistingWindCap	solved.ExistingWindCap[n1] else: 0
Pmax	solved.Pmax[n1]

Parameter	Row value (Node n1, nodes [1,n])	Column value (nodes [1,n], Node n2)	Diagonal value (Node n1, node n1)
ExistingArcs	0	0	0
PotentialArcs	1	1	0
Fmax	Fmax (Static value in settings)	Fmax (Static value in settings)	0
Fmin	Fmin (Static value in settings)	Fmin (Static value in settings)	0
ArcCost	Distance n1 to nX * Nominal cost (Settings)	Distance n2 to nX * Nominal cost (Settings)	0

Parameter	Row value (Node n1, TimeHorizon[1,t])
ExCapA	solved.ExEnCon[n1, tx]
ExCapB	solved.EnSold[n1,tx] + solved.ExEnRen[n1,tx] + solved.ExPotA[n1,tx] + solved.ExPotB[n1,tx]
Dem	0
PercDem	1
PercW	Same value as other row in the existing matrix (All rows are the same)

Figure 2: Update matrix procedure

potential connections between the current and the new nodes. Therefore, the cost of these new connections has to be computed using the geographical distance and the nominal cable cost. This cost is determined by the company based on the terrain and the type of cable. Once this is fixed a kilometer based cost is evaluated to join different points of power supply. Figure 2 describes all the parameters that need to be updated and the solution variables used to update these parameters. Furthermore, the update procedure with the values obtained from the other microgrids is different for each parameter in the microgrid. Few specific parameters condition the values collected with the solve of isolated microgrids. When one of these special parameters are positive in a node, all the values of this node are collected, if elements are existing in this collected node, they are copied to the solution too. The parameters for select new nodes are $ExEnRen$, $ExEnCon$, $EnSold$, $ExPotA$ and $ExPotB$. The relation between these parameters and the next microgrid is specified in the update figure 2. For vector parameters, the update is easier. Vectors expand their dimensions based on the parameter of their length. A vector based on nodes will expand as many nodes as new nodes are in the update values.

The simple way to solve this network is to evaluate all the possible permutation of elements and choose the optimal one (horizontal method). Nevertheless, this method is useless and can not be scaled, the complexity increase exponentially with the number of nodes. That means solving a combinatorial explosion problem that increases with the number of nodes in the system. In this context, real company networks cannot be solved due to the high complexity and the amount of time required to address the solution of the model. Note, that for this horizontal method we need to evaluate n! of combination where n is the number of nodes.

The method presented in this work is an attempt to address this issue vertically to reduce the complexity to n. Therefore, we propose to evaluate each microgrid only ones concerning the information of all the other nodes in the network. The vertical update procedure is based on using the optimal solution of all the microgrids except one to update the information of this isolated microgrid. Thus, instead of having only a solved instance to be used in the update algorithm we use (n-1 solved instances).

4.1. Serial procedure

Algorithm 1 depicts the main steps required to solve the problem vertically. First of all, we need to initialise all the microgrids using initial information and create the model instances. In order to set a perfect competition concerning the Nash equilibrium theorems, the energy prices are derived as the marginal cost of production. The marginal cost of production is also known as the shadow price or dual of the mass balance constraint. It can be defined as the unitary cost for an additional unit of production at any node. This way, a nodal pricing based market is formed within a microgrid. Each microgrid is considered as one zonal market. However, prices are only set for energy interaction among microgrids thus derived from a nodal-prices of the sending microgrid. Therefore, we need to presolve a relaxed version of the model, considering all the variables discrete to obtain the shadow prices of the node balance constraints. This information has to be introduced in the priceB parameter of the instance. After that, we resolve all the instance using an optimizer solver such as CPLEX, Gurobi or EXPRESS. Then, the optimal solution is stored. Once all the individual solutions are obtained we update each instance using the vertical update procedure described above. Finally, we store the combination with the best profit.

Algorithm 1 Collaborative Microgrid Resolution Method (R-CoMG)

$currentProfit = 0$
$bestProfit = 9999999$
$PN = mg1, mg2, \dots, mgN$
for all mg in PN **do**
    Generate the mg model.
    Relax the mg considering all variable in the continuous space.
    Obtain the shadow prices for the node balance constraint.
    Update the priceB parameter using these duals.
    Solve the update mg model.
end for
for all mg in PN **do**
    Update mg using the vertical update procedure concerning the optimal solution of all the others microgrids in PN.
    Solve the new mg instance.
    Store the current profit.
    if $bestProfit \leq currentProfit$ **then**
        $currentProfit = bestProfit$;
    end if
end for

4.2. Parallel procedure

The serial procedure requires solving different instances and perform different operations such as the vertical updated. Therefore, we propose a parallel schema that minimizes the task dependency and maximizes the use of the computing resources.

In the serial algorithm, solving a combination represents solving each node on the combination considering the solution of previous nodes. Thus, we design a method

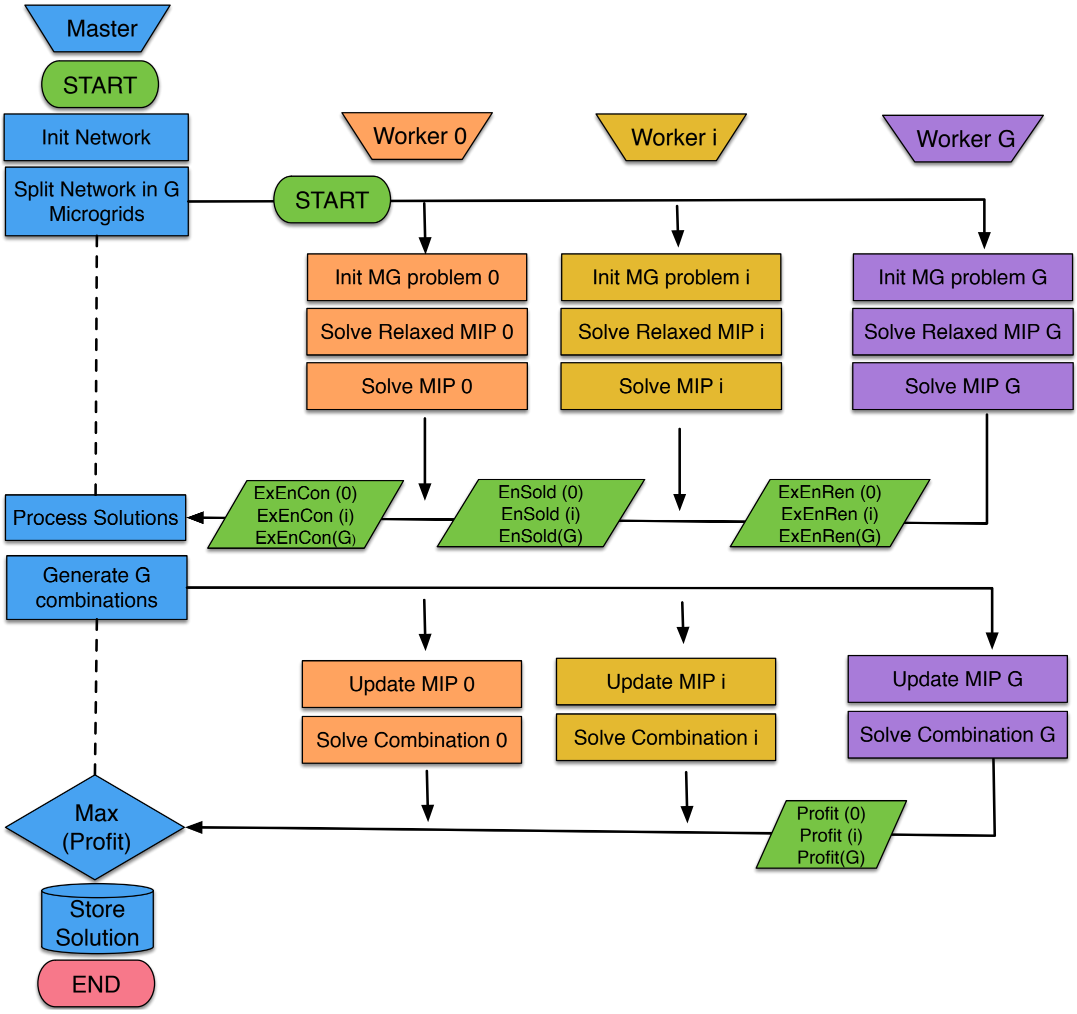


Figure 3: Master-Worker implementation schema.

that allows solving all the nodes belonging to a combination in parallel in different machines with the exception of the last node that waits for gathering all the solutions to update itself and solve considering all the previous nodes solutions. Figure X describes the functional diagram of the proposed parallel tool which follows the Master-Worker paradigm.

There exist different paradigms for implementing Master-Worker applications. In this work, MPI4Py is the library selected to code the Master-Worker.

Firstly, the Master process is executed to iterate and manage all the combinations. Next, as many Worker as there are microgrids is created and stored in different text files in a shared file server. Once, the microgrids are created, the Master sort all the microgrids in a particular order to form a combination. A Worker solves each microgrid concurrently. Nevertheless, the last microgrid in the combination is not solved now. Master gathers all the solution and then the resolution of the last microgrid starts considering all the previous solutions. After that, the master compares the current solution with the best solution stored and update or not this value. If there is another combination available, the procedure starts again.

5. Decision Support System (DSS)

The Decision Support System proposed in this work aims to automate all the steps required to deal with the novel mathematical model presented in previous section 3.1. Note, that the architecture we propose is flexible and general and can be adapted or extended to other prescriptions or predictions models related to GTEP problems. The architecture proposed deals with all the data belonging to GTEP problems and also with other data that can be integrated to model better the current situation of energy generation and client consumption. One of the main reasons for developing a DSS is to transfer the research knowledge and academic innovation to the society. This way, we bring a tool that helps companies in the field to make better operational, tactical and strategical decision.

The DSS is merged with cloud computing to avoid the barrier of software installation and maintenance inside the companies computers. Moreover, a cloud-based service can perform software updates seamlessly and can deliver a generic product that can be used by everyone independently of the knowledge in data-science. Therefore, the DSS proposed in this work is designed as a Software-as-a-Service (SAAS). The client is the visual part of the application; where the decision-makers interact with uploading the parameters, performing executions and exploring results. The client has been implemented using a trendy technology, Angular 5 [47]. Then, the server or the business logic is implemented using different technologies such as Node.js [48] to interact with the client, Python 3 [49] scripts to automate the integration tasks, the resolution of the problem and also the interaction with the mathematical model. In addition, different R scripts[50], belong also to this layer.

To begin with, the DSS has a data layer to integrate public and private data. These data are merged and integrated to obtain a model very close to the real processes of the company and also very similar to the current context. The data integration is made using python scripts to extract data and adapt to the Pyomo mathematical model. Next, the data processing stage is about data cleaning, filtering and data transformation to make the prescriptions feasible. After that, a parallel framework runs the method described in Section 4.2 and solve the GTEP problem. Figure 5 depicts the main parts of the architecture described. To keep the focus of the project, the application offers the main results obtained and required to support decision making using charts and an interactive network to explore the solution.

This information is of great interest to power industry either power suppliers and customers. The optimal network allows power suppliers to know which are the best clients to satisfy. Otherwise, clients can evaluate if they want to make a connection to a supplier or invest in installing new generators. This information has a clear strategical focus for both companies and clients. Furthermore, knowing the status of the batteries and generators can help distribution operator centre in their daily tasks in the maintenance of the microgrid. Finally, from a tactical point of view, the power supplier can evaluate how many energy the should produce at each period to maintain the service available.

The main features of the decision support system designed can be summarized as:

- **Data integration:** The DSS proposed can be fed with public and private data coming from sensors, databases, or indeed current software tool. Section 5.2 expands this information describing the methodology used in this work to deal with this set of heterogeneous data.

- **Data processing:** The DSS proposed aims to process after and before computing the optimal solution. Section 5.3 shows the (pre-processing) procedure to transform the data, and the Section 5.4 shows the method to display the solutions (post-processing).

- **Optimal prescriptions:** One of the novel features of the DSS presented in this work is the capability of making recommendations. These recommendations are based on the execution of a complex mathematical model that is able to obtain the optimal network taking into account real conditions.

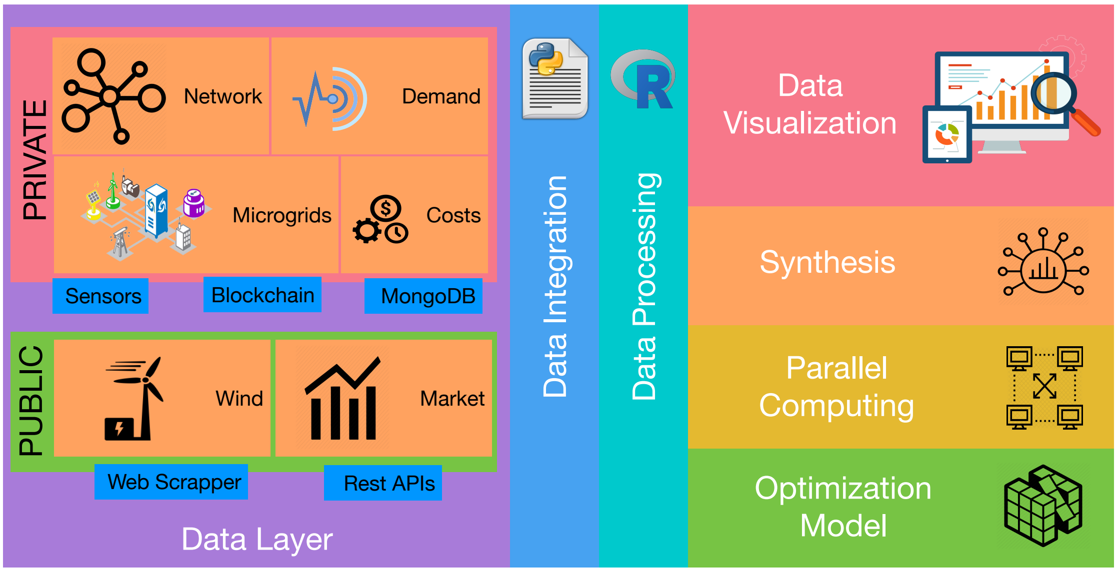


Figure 4: Decision Support System architecture.

- **Scenario Analysis:** Another important contribution of this work is the capability of simulating and analyzing different scenarios. The distribution system operator can evaluate what is going to happen if new links or nodes are introduced to the system and how the system evolves from this point. Besides, strategical decisions of choosing the right place to build new generators can be evaluated using this function. This feature helps to anticipate and mitigate the undesired effects of some decisions.

These features are achieved after automatizing and encapsulating the DSS workflow presented in Section 5.1.

5.1. DSS workflow

Figure 5 illustrates the three stages of the decision making process with DSS proposed. The preliminary step is pre-processing where the input data is gathered from different sources and process to feed the mathematical model. First of all, the information is collected to build the power network. Once the power network is built, is time to smartly break-down to multiple sub-networks. At the same time, public real-time data is obtained from APIs and WebScrappers to model the current context. For instance, weather data or data related to renewables production. After that, all this data is integrated into the mathematical model. In addition, the data is also transformed and manipulated as explained in Section 5.3.

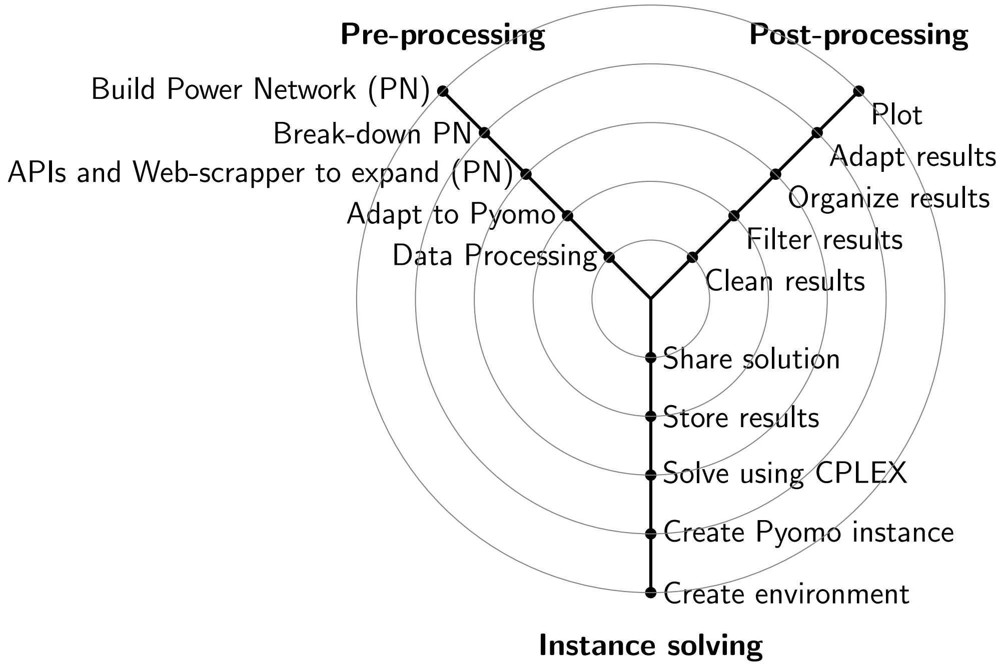


Figure 5: DSS-workflow

Next, the instance solving stage starts, this stage involves running the parallel method proposed in this manuscript to solve all the iterations required to obtain the optimal solution to the problem. First of all, a virtual cluster is deployed in the cloud. Then, the algorithms perform the resolution using CPLEX. Finally, the results are cleaned, filtered and organized for interactive visualization. The decision making entity performs a here and now decision for the power network expansion through either capacity or transmission line. The increase in demand or sub-par utilization of the production capacity are one of the primary reasons for an expansion. The decision maker would visualize this relation to confirm new investment budgets. In comparison to traditional model method the user can see the information of the parameters variables and change relationships in one window.

5.2. Data Integration

In this section, we propose a methodology based on data integration to automate the process of dealing with the decision support system and also, to solve the following challenges: (i) the data comes from different sources and formats. (ii) the electrical networks are commonly stored in non-relational databases. (iii) the data is large, complex and dirty.

The decision support system presented in this paper needs to access data stored in different formats, from different access profile and originated from different sources to achieve optimal decisions and support the decision making process.

First of all, companies have data stored commonly in non-relational databases such as MongoDB with private data about they clients network. In this context, to facilitate the usage of the model by companies, the communication with other resources and databases, and also to be able to automate the overall process, the authors propose to use a standard based on JSON to model the input and the output related to GTEP problems. This way, the decision support system can be easily integrated with current market tools.

```
Type: battery
 {
   "% efficiency":0.7,
   "existing capacity",
   "maximum capacity":,
   "minimum capacity":,
   "% discharge":,
   "life":,
   "cost":,
   "operational cost":
}
```

```
 Type: generator
{
  "existing capacity":100,
  "minimum on":3,
  "minimum off":3,
  "cost":0.2,
  "cost on":0.2,
  "cost start":0.2
}
```

The input data of a GTEP problem needs at least 3 schemas to feed the DSS. First of all, a scheme to build the network connections and attributes. In this case, we store the links between nodes and the cost of the links. Next, we use another scheme to represent the nodes with geographical information (latitude, longitude), physical propeerties (demand. investment and capacity) and information about the elements that compound the node: batteries, wind generators or conventional generator. For each element, it is stored its physical properties. The following JSON schema describes the required parameters to model the behaviour of batteries and generators.

Finally, we propose a schema to take advantage of clustering methods to speed up the resolution of the network.

5.3. Data processing

Electrical companies around the world have much information that comes from customer sensors. Thus, they have large sets of historical data that can be used to make accurate predictions about future demand. Nevertheless, this data comes from different sensors so needs first to be clean by removing negative values, NaN or 0 values. Moreover, a large set of data implies very high-resolution times. Thus, the optimization model needs a reasonable bunch of data to get the best trade-off between the accuracy of the solution and the computational effort. Hence, we produce a smaller bunch of data by reducing the time-horizon model transforming the incoming demand files.

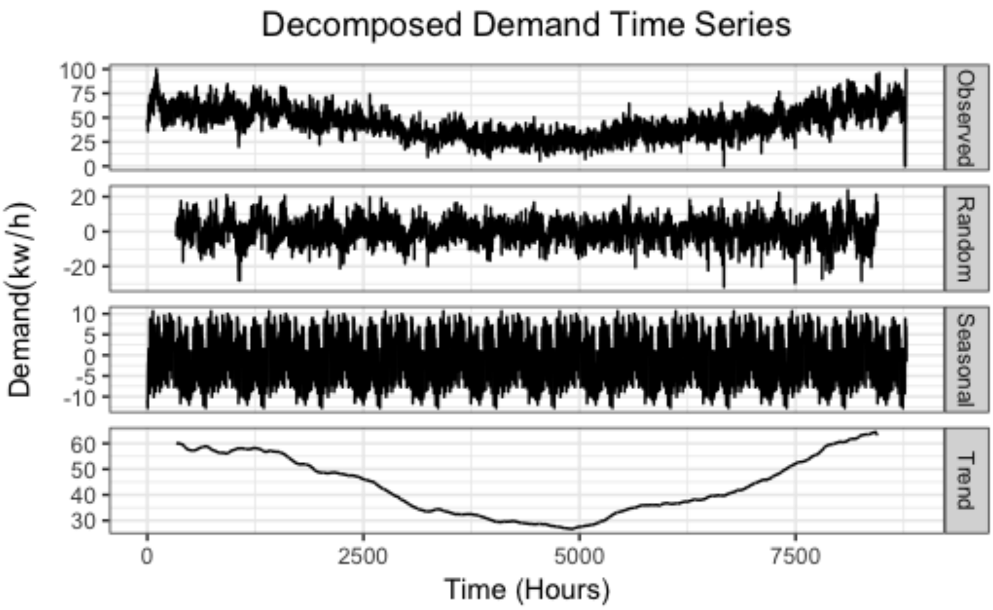


Figure 6: Demand seasonality and complexity

The historical data of electric demand is strongly seasonal and vary a lot depending on the day and the hour as can be seen in Figure 5.3. Therefore, we develop some R routines to generate 4 typical weeks. One week representing each season. This way, we are able to reproduce the hour day and season variations and obtain a bunch of data that can be easily solved by the optimization model.

Finally, once the private data is gathered and files related to the demand are cleaned and transformed, is turn to combine this information with public information coming from APIs such as *Renewable Ninja* [1] and from other web pages using python web scrappers to obtain the information about wind and market in real time. This information builds the real situation where the model needs to provide support. Note, that the expansion of the renewable production depends on location. The system operator needs to decide the site, the technology and other features of a new wind park where the expansion could take place. This information is not static and changes depending on different circumstances. The same happens with the market. Therefore we need to keep track of this changes using real-time information every time we run the model.

5.4. Data Visualization

The platform also allows decision makers and companies to easily explore, analyze graph data and optimal solutions in an interactive network by selecting nodes in the graph and explore the evolution of the components in chart and plots. This way, decision-makers can spot nodes/subgraphs through interactive comparisons across a a wide range of graph properties. Intuitively, the application highlights the most interesting results such as the optimal profit, the investments and the costs. Moreover, all the nodes belonging to the optimal solution are coloured using purple colour to help decision makers to compare and understand the changes between the initial or current network and the optimal one. The interactive data analytics platform is flexible and has many potential applications and use cases. For instance, it has shown to be useful for understanding the optimal solution through interactive comparison across a wide range of charts and plots that describe the evolution of the elements. This way, decision-makers can explore the activity of batteries and generators along the network and check the most important statistics in charts. In addition, the application assists also in the evaluation of power-sharing. We also provide many other interactive analysis tools to evaluate the influence of the market and the demand on the optimal network. Moreover, the edges of the network provide essential information about the energy flow and the costs. Finally, the tool also leverages graph sampling methods to ensure fast and efficient loading and processing of the data. Figure 5.4 shows a use case of the dashboard developed to explore the solution data.

[1] https://www.renewables.ninja/documentation/api

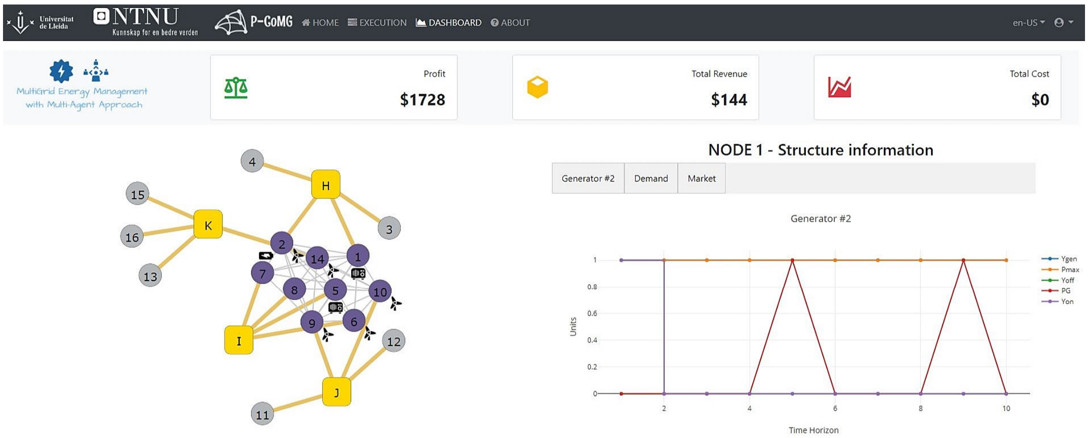


Figure 7: Dashboard. Interactive optimal network.

6. Case study

6.1. Intended use of the model

The model can assist the short-term expansion decision making for distribution system operators (DSO). The DSO also has the flexibility to decide the regions or microgrids. In one country usually, there is one transmission system operator but many more distribution system operators. For example, in Norway, there is only one Statnett that is a TSO, but there are more than 400 DSOs [2]. In this scenario, a bottom-up approach is more practical because each DSO only has control over a specific geographical region, unlike the nation-wide DSO. This way, a power network can be decomposed into several microgrids. This way, the DSO evaluates the investment in different scenarios, such as increasing or decreasing demand and generation units. For instance, the DSO can evaluate the impact of a sudden increase in demand in some location. Apart from that, the location of generation units can be optimised based on the local, political or economic scenarios.

The DSO can also use P-CoMG to perform investment decisions in a region. The investment can be regarding a generation unit, battery unit or a new connection between two substations. With sensitivity tests considering different sizes and regions the tool can determine the undesirable effects of these decisions. For example, the grid can decide to relocate a generation unit because the neighbouring DSO has placed significant generation units in one location. In the same scenario, the DSO can

[2]https://www.nve.no/energy-market-and-regulation/network-regulation

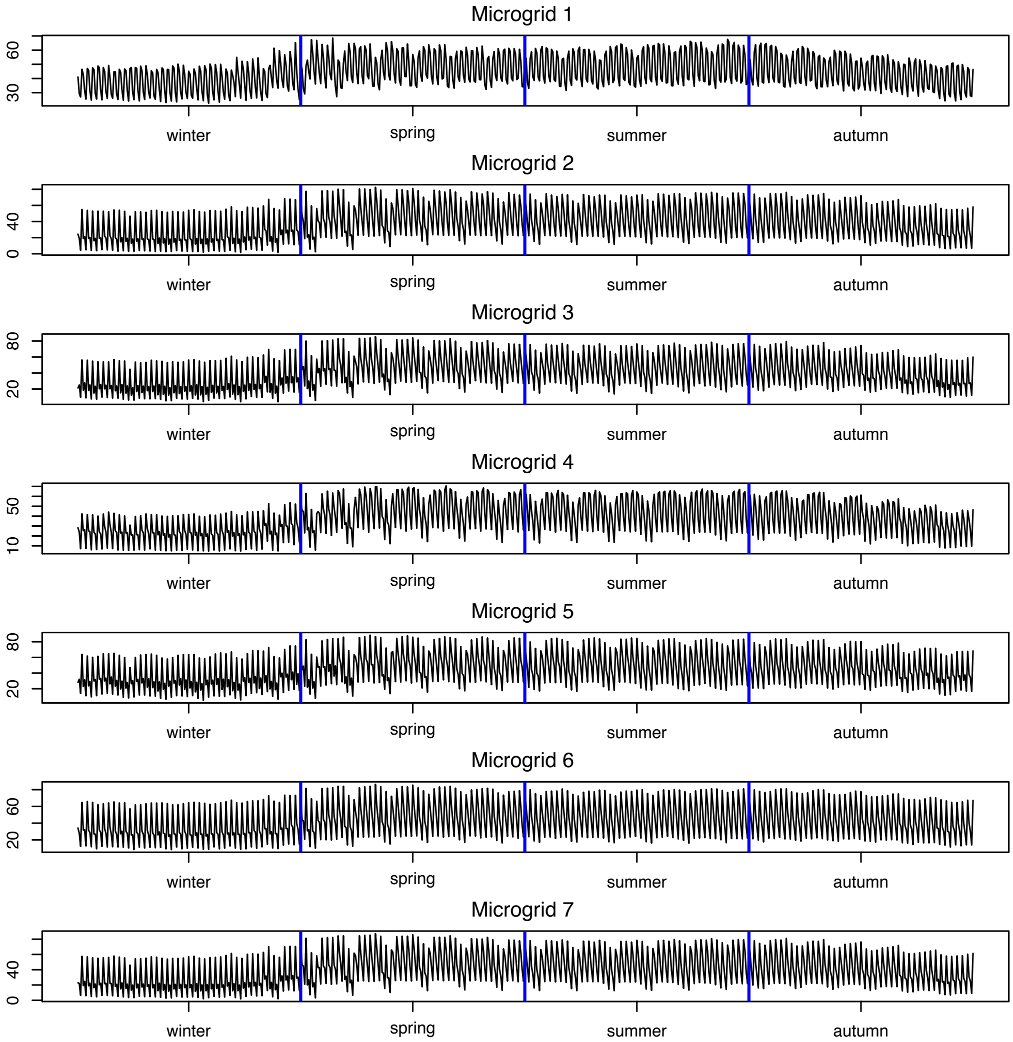


Figure 8: Evolution of the customer's demands per season and microgrid.

determine whether or not to connect to the neighbouring grid. There is a substantial reduction in the total investment due to the replacement of a new generation unit with a transmission line.

The DSO can interactively explore the network and check different solutions in one window using P-CoMG, comparing different solution the DSO can evaluate the evolution of the network in different situations and perform corrective actions. Figure 8 depicts the evolution of demand and can help to determine patterns and extract information.

In the current energy transition, the demand side participation (DSP) is a significant event. In this case, within a DSO there will be potential generation units (PV panels) or demand controls. In P-CoMG this feature can be studied the same way considering different regions with more or less flexibility.

6.2. Scalability Analysis

In this section, we evaluated the performance of the parallel implementation of R-CoMG, according to different problems.

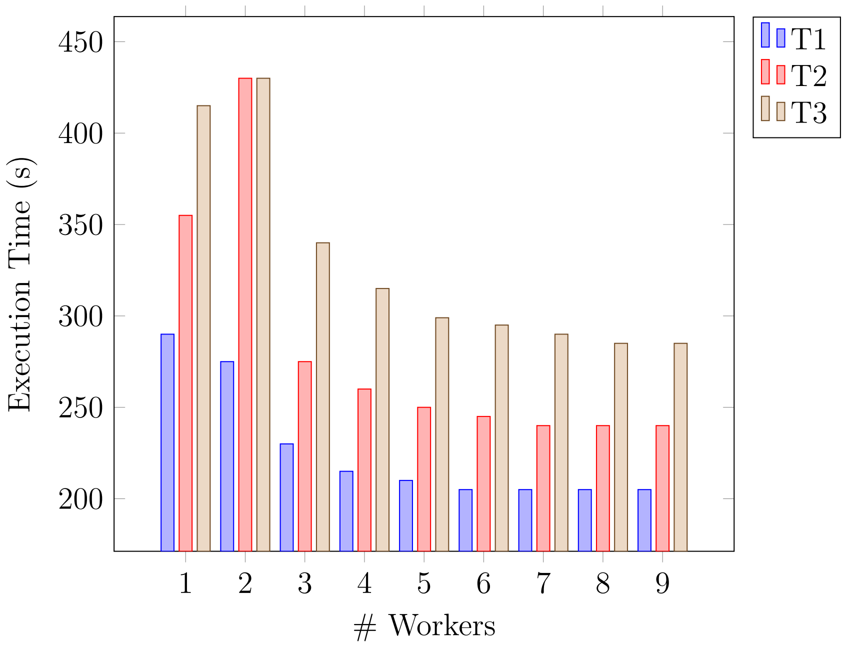


Figure 9: Scalability analysis

These problems has been made to test the correctness of the update procedure and to evaluate the optimal solution. Table 6.2 shows the dimensions of the test-bed.

Tests were conducted in the Stormy cloud platform deploying a virtual cluster.

Instance	# Microgrids	# Batteries	# Generators	# Wind Plants
T1	6	6	6	10
T2	7	7	6	13
T3	8	7	8	14

Figure 9 depicts the advantages of using the parallel implementation to reduce the execution time. The serial algorithm beats the parallel implementation only when the number of workers is equal to 2 due to the delay in communication between the Master and Worker processes. In the other cases, we can see that the execution time decrease while we add more workers. Finally, the method gets saturate when we have more workers that combinations to solve. So, the maximum power of the method is when we have one worker for each microgrid solving in parallel.

7. Conclusions and Future work

The novelty of this research is the development of a practical, flexible and scalable DSS to support the multi-purpose decision-making process for the power distribution network. The presented model P-CoMG integrates the optimisation model and the DSS together to provide the ease of use and tractability. The primary capabilities of P-CoMG are the integration, the automation and the use of high-performance computing to offer a smart and robust service. The results prove the advantages of using parallel computing to split and resolve the problem. Moreover, the DSS assist decision makers in the evaluation of future investments, maintenance of the optimal network and control the energy flows. The service presented in this work has much potential because of is a web application, accessible with all devices from anywhere. Thus, the service presented in this article is a potent seed for a much bigger service with great potential to become a reference in the power network companies.

Merging the potential of cloud computing, high-performance computing and optimisation models with usability and portability makes the decision-maker life more relaxed and comfortable. This way, the process of making a strategical, tactical and operational decision becomes easy. Moreover, P-CoMG is a tool for solving power distribution network expansion problem from a bottom-up point of view.

Regarding the future work, it is essential to highlight the ability of the model to simulate different scenarios. Implementing further this feature will allow decision-makers to make better strategic decisions. Furthermore, another critical work to improve is to introduce into the DSS the real terrain and cable properties to a better understanding of the optimal situation. This way, this information can be used to feed a neuronal network to predict the arc cost of a new connection regarding distance, terrain, cable properties and more. This capability can increase the ability of the DSS to inspect and evaluate more situation. Another enhancement concerning reliability is to introduce the usage of the brooks-iyengar algorithm with Byzantium fault tolerant theory. Finally, another direction is improving the mathematical model considering uncertainty and building a stochastic multi-horizon model regarding hourly demand variations and yearly investments in sharing production. In a successive paper, the authors would introduce a reliability perspective of power network followed by automation of the region formation algorithms.

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Appendix A. Nomenclature

Nomenclature

Sets

N	Nodes.	$i, j \in N$
G	Conventional generators.	$g \in G$
W	Wind power plants.	$w \in W$
S	Battery types.	$s \in S$
T	Time window.	$t \in T$

Grids

N_{nodes}	Number of nodes.	Par($\mathbb{Z}^+$) (✍)
$b_{i,j}$	Admittance of the arc between nodes i and j.	Par($\mathbb{B}$) (✍)
$Fmin_{i,j}$	Minimum power flow between nodes i and j.	Par($\mathbb{R}^+$) (✍)
$Fmax_{i,j}$	Maximum power flow between nodes i and j.	Par($\mathbb{R}^+$) (✍)
$ExistingArcs_{i,j}$	Existing arc among nodes i and j	Par($\mathbb{B}$) (✍)
M	Big M.	Par($\mathbb{Z}^+$) (☞)
$F^t_{i,j}$	Flow between nodes i and j at time t.	$Var(\mathbb{Z}^+)$
V^t_i	Voltage angle of node i in time t.	$Var(\mathbb{R}^+)$
$dir^t_{i,j}$	Direction of flow from node i to j at time t.	$Var(\mathbb{B})$

Conventional

N_{gen} Number of generators. Par($\mathbb{Z}^+$) (✍)

$ExistingConvGen_{g,i}$ Existing generator g at node i. Par($\mathbb{B}$)(✍)

Cg Operational cost (€/kwh) for a conventional generator plant. Par ($\mathbb{Z}^+$))(✍)

C_{on} Operational keeping on (€/kwh). Par($\mathbb{R}^+$) (✍)

C_{start} Operational start (€/kwh). Par($\mathbb{R}^+$) (✍)

$Pmin_g$ Minimum power produced (kWh) in generator g. Par($\mathbb{R}^+$) (✍)

$Pmax_g$ Maximum power produced (kWh) in generator g. Par($\mathbb{R}^+$) (✍)

$MinOn_g$ Minimum on time for generator g. Par($\mathbb{Z}^+$) (✍)

$MinOff_g$ Minimum off time for generator g. Par($\mathbb{Z}^+$) (✍)

$Yon^t_{g,i}$ Activation of generator g at node i through time t. Var($\mathbb{B}$)

$Yoff^t_{g,i}$ Deactivation of generator g at node i through time t. Var($\mathbb{B}$)

$Ygen^t_{g,i}$ Status of generator g at node i through time t. Var($\mathbb{B}$)

$PG^t_{g,i}$ Production of a generator g at node i through time t. Var($\mathbb{R}^+$)

Wind

N_{wind} Number of wind plants. Par($\mathbb{Z}^+$) (✍)

$ExistingWindCap_{w,i}$ Existing wind power plants w at node i. Par($\mathbb{Z}^+$) (✍)

$InvW_i$ Investment cost (€) for a wind plant at node i. Par($\mathbb{R}^+$) (✍)

$maxWcap_i$ Maximum capacity that can be installed at node i. Par($\mathbb{R}^+$) (✍)

$PercW^t_i$ Percentage that can be produced at node i at time step t. Par($\mathbb{R}^+$) (✍)

$LifeWind$ Nominal life span of wind plant. Par($\mathbb{R}^+$) (✍)

$PW^t_{w,i}$ Power produced (kwh) in plant w at node i through t. Var($\mathbb{R}^+$)

$PNW^t_{w,i}$ Production of newly installed wind plant (kwh) at node i in time t. Var($\mathbb{R}^+$)

Battery

N_{bat} Number of batteries. Par($\mathbb{Z}^+$) (✍)

$LifeBat$ Nominal life span of battery. Par($\mathbb{R}^+$) (✍)

$Cbat_s$ Installation cost (€/kWh) of battery s. Par($\mathbb{R}^+$) (✍)

$Obat_s$ Operational cost (€/kWh) of battery s. Par($\mathbb{R}^+$) (✍)

$Ebat_s$ Efficiency of battery s. Par($\mathbb{R}^+$) (✍)

$MaxBat_s$ Maximum capacity of battery s. Par($\mathbb{R}^+$) (✍)

$MinBat_s$ Minimum capacity of battery s. Par($\mathbb{R}^+$) (✍)

$RateBat_s$ Rate of power extraction of battery s. Par($\mathbb{R}^+$) (✍)

$Existbat_{s,i}$ Existing, quantity of battery s at node i. Par($\mathbb{B}$) (✍)

$PotBat_{s,i}$ Potential of battery s at node i. Var($\mathbb{Z}^+$)

$CharBat^t_{s,i}$ Energy status of a battery s in node i through time step t. Var($\mathbb{Z}^+$)

$QtyBat_{s,i}$ Quantity of battery s at node i. Var($\mathbb{Z}^+$)

$XBatIN^t_{s,i}$ Energy flow into a battery s in node i through time step t. Var($\mathbb{Z}^+$)

$XBatOUT^t_{s,i}$ Energy flow of a battery s in node i through time step t. Var($\mathbb{Z}^+$)

Potential Grid

$PotentialArcs_{i,j}$ Potential arcs between nodes i and j . Par($\mathbb{B}$) (✍)

$ArcCost_{i,j}$ Cost (€) of connecting i, j. Par($\mathbb{R}^+$) (✍)

$LifeCables$ Life time of the cables/arcs among i, j. Par($\mathbb{R}^+$) (✍)

$Y_{i,j}$ Potential arc between i and j. Var($\mathbb{B}$)

Exceeding Capacity

$ExcCapA^t_i$ Exceeding capacity from conventional at node i through time t. Par($\mathbb{R}^+$) (✍)

$ExcCapBi^t$ Exceeding capacity from renewable at node i through time t. Par($\mathbb{R}^+$) (✍)

$PriceA^t$ Operational cost (€) from conventional at time t. Par($\mathbb{R}^+$) (✍)

$PriceA^t$ Operational cost (€) from renewable at time t. Par($\mathbb{R}^+$) (✍)

$FlowA^t$ Flow from conventional at time t. Var($\mathbb{R}^+$)

$FlowB^t$ Flow from renewable at time t. Var($\mathbb{R}^+$)

Price/Demand Costs

Dem_i^t Demand at node i through time t. Par($\mathbb{R}^+$) (✍)

$Elprice^t$ Electricity price at time t. Par($\mathbb{R}^+$) (✍)

$MarketPrice_t$ Market price at time t. Par($\mathbb{R}^+$) (✍)

$EnSold_i^t$ Energy sold at time t. Var($\mathbb{R}^+$)

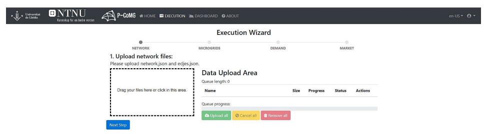
$ExEnCon_i^t$ Exceeding energy from conventional at time t. Var($\mathbb{R}^+$)

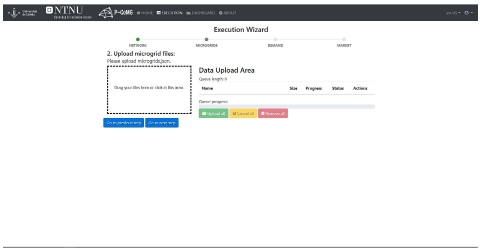
$ExEnPotA_i^t$ Potential exceeding energy from conventional at time t. Var($\mathbb{R}^+$)

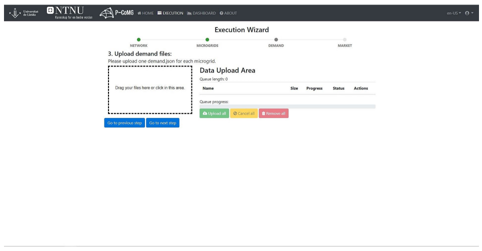
$ExEnPotB_i^t$ Potential exceeding energy from renewable at time t. Var($\mathbb{R}^+$)

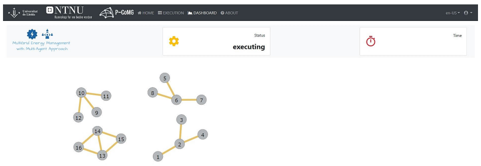
$ExEnRen_i^t$ Exceeding energy from renewable at time t. Var($\mathbb{R}^+$)

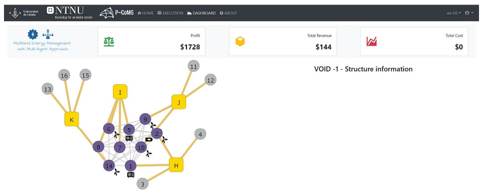
Appendix B. Decision Support SystemS (DSS)

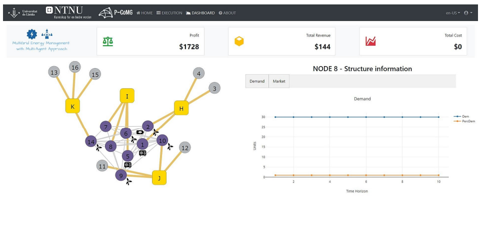


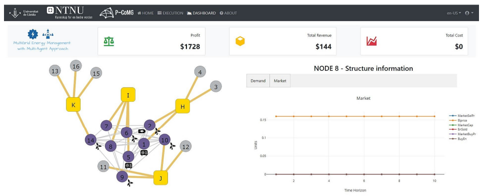

NTNU
Execution Wizard
2. Upload microgrid files:
Data Upload Area


NTNU
Execution Wizard
3. Upload demand files:
Data Upload Area


NTNU
executing


NTNU
$1728
$144
$0
VOID -1 - Structure information


NTNU
$1728
$144
$0
NODE 8 - Structure information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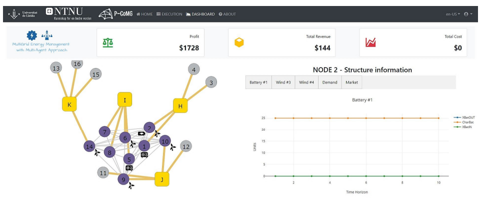
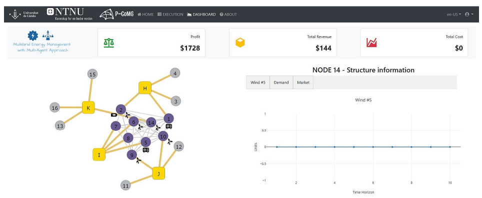
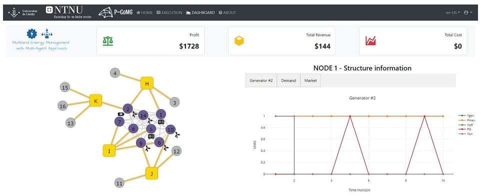
$1728
$144
$0
NODE 8 - Structure information


NTNU
$1728
$144
$0
NODE 2 - Structure information


NTNU
$1728
$144
$0
NODE 14 - Structure information


NODE 1 - Structure information
Generator #2
Demand
Market
Profit
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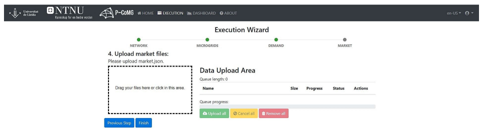
Total Revenue
$144
Total Cost
$0


Execution Wizard
4. Upload market files:
Please upload market.json.
Drag your files here or click in this area.
Data Upload Area
Queue length: 0
Name
Size
Progress
Status
Actions
Queue progress:
Previous Step
Finish